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COTTON PLANTS DISEASE IDENTIFICATION USING IMAGE SEGMENTATION AND MACHINE LEARNING

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Abstract

In India's agricultural economy, cotton is one of the most crucial cash crops. It plays a vital role in the livelihoods of over 6 million farmers, contributing significantly to their income and sustenance. Despite its importance in India's agricultural economy, cotton cultivation faces a significant disadvantage in the form of high susceptibility to pests and diseases. Research shows that approximately 30-35% of the cotton crop yield is prone to contamination, highlighting the need for effective pest and disease management strategies to ensure optimal crop yield and quality. The timely identification of diseases in cotton cultivation is crucial since detecting diseases at an advanced stage often results in crop failure. However, recent computer vision and machine learning advancements present a promising solution that can significantly impact the agricultural industry. By leveraging these technologies, farmers can identify and address crop diseases early on, enabling them to take corrective measures to prevent crop failure and increase yield. The symptoms of most diseases affecting cotton plants are typically visible on the leaves, flowers, and fruits. In a recent research study, multiple studies were reviewed, which utilized image pre-processing, segmentation, and machine learning techniques to identify and categorize various diseases to distinguish peculiar cotton diseases. The study's findings suggest that advanced machine learning approaches outperform commonly used image processing methods in terms of accuracy and other proper measures. The study aimed to identify and classify disorders affecting cotton leaves, providing a potential solution for early disease identification in cotton cultivation. The results reveal that the model distinguishes healthy and unhealthy cotton leaves.

After classifying all the diseased cotton plant leaves, the objective is to identify the complete diseased portion of that leaf. Study shows transfer learning techniques gives better result for segmenting affected portions on leaves. Results show Faster RCNN and Single Shot Detector (SSD) algorithms give better performance for portion identification

as pre-trained model changes. Results show that Faster R-CNN-VGG16 outperformed SSD-VGG16 and SSD-Mobile Net in terms of accuracy.

The field that has the most significant impact on people's lives is agriculture. Most farmers experience leaf disease issues, resulting in decreased agricultural output. Farmers face difficulty identifying and treating leaf diseases due to inadequate information, resulting in a significant loss of agricultural output. The lack of knowledge and awareness about the various diseases affecting cotton plants makes it challenging for farmers to take corrective measures in a timely and effective manner, ultimately impacting crop yield and quality. Healthy nutrition can only be attained if the food yields are robust. After identifying the diseased portion, the same disease class is categorized more quickly and intelligently, assisting farmers in keeping an eye on their fields and lightening their workload. This method focuses on masking the diseased portion and identifying the corresponding disease class. This approach uses CNN and its classification head to predict the disease, and Mask RCNN is used to mask the precise parasite hosted by the leaf. Transfer learning is performed when a dataset is trained with the Mask RCNN model with ResNET-101. The model's output recognizes the name of the disease in the affected region and accurately identifies it.

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Chapter 1

Introduction

Most agricultural nations, like India, have relied heavily on agriculture for their financial prosperity. The North of India is where cotton is primarily grown [1]. Several diseases have negatively impacted cotton plant productivity over the past few years. The admission of the infection and its preparation are the most crucial requirements. To reduce losses to the cotton plant leaves, plant diseases need to be accurately diagnosed and treated as soon as possible [2]. It is good knowledge that farmers identify the disease too late, making treatment extremely challenging and expensive. Due to the difficulty of producing a significant number of professionals nationwide, the lack of nearby experts is the primary cause. As a result, farmers may benefit from the availability of computer-based expert programs. This study aims to develop a system that empowers farmers to obtain insights on cotton plant leaf diseases by uploading pictures to a central authority with specialized expertise. The proposed system offers a practical solution to the challenge faced by farmers in identifying and treating leaf diseases, thereby enabling them to take appropriate measures promptly and mitigate the adverse effects of diseases on crop yield and quality [3]. The farmers will receive diagnostic technologies in this way from human experts. To ensure that the disease can be recognized in enough quantities on photos, the computer scientist will utilize this information to generate a training set that will be applied to the images. The pattern-matching algorithm will be created to quickly and accurately identify the disease in its earliest stages. Detecting diseases by examining their physical characteristics is known as cotton leaf disease diagnosis. Feature extraction removes identifiable structures from digital images [4]. Several feature

descriptors can be used in this process. The feature is checked once feature descriptors are passed to a separator. An algorithm called a ”separator” categorizes an element based on its similarity to the training database. The features in the training database were previously not included in known objects.

1.1 Challenges

Automation of the process of diagnosing diseases has not yet been thoroughly examined. The goal of this study is to pinpoint some of the most significant issues, investigate their root causes and how they affect the effectiveness of the techniques that have been previously proposed, and then suggest some potential directions that could be taken to lessen or completely eliminate their adverse effects. The following problems were determined to be the most significant ones:

1. The difficult-to-control capturing settings may result in photographs displaying difficult-to-predict features, complicating illness identification [5].
2. It can be challenging to properly isolate the region of interest where the symptoms are visible when the background contains elements that could contribute to this difficulty [6].
3. A particular disease may have varied features depending on the development stage and, in some cases, where it is on the plant [7].
4. The majority of symptoms gradually blend into healthy tissue rather than having sharp borders, making it challenging to distinguish between healthy and diseased areas [8].
5. Because distinct diseases may create symptoms that are visually similar to one another, strategies for differentiating between them must rely on extremely slight differences [8] [9].
6. Multiple diseases may create symptoms simultaneously, appearing physically distinct or mixed into a ”hybrid” symptom that is challenging to diagnose [8] [9].

1.2 Motivation

The textile industry is essential to the economy of a developing country like India. Shirpur City in Maharashtra is a major textile center. Shirpur Textile Park contains 800 shuttle-less looms that produce 1.5 million meters of cotton fabric daily. Cotton is supplied by about 3 lakh farmers in and around Dhule district. Rainwater collecting has reduced the groundwater level in the entire area from 3000 feet to 50 feet, boosting cotton yield. Its production has grown. Shri. Amrishbhai Patel, the Chancellor of SVKM's NMIMS and a former Education Minister, is working tirelessly to promote this to rural drought-prone areas across the country. With the help of the farming community in the Dhule district, the Shirpur irrigation pattern is established with the use of 200 check dams. The Chief Minister of Maharashtra highly values this pattern. After examining this pattern, it has been discovered that Shirpur Pattern has greatly aided in increasing Cotton production. However, there is a scope for improvement of cotton crop quality. Cotton's major product is fiber, often known as lint. Fiber length, strength, fineness, maturity, and homogeneity are all factors in fiber quality. The cotton crop is susceptible to a wide range of diseases and insect pests, which can cause substantial reductions in yield. This study discovers early detection and recovery of certain diseases. It can aid in the overall growth of cotton crops. It will also improve the quality of Cotton and add value to the items. Farmers should be aware of the cotton leaf disease as soon as possible to treat the damaged cotton plants quickly. Transfer learning techniques like CNN, Faster RCNN, SSD, and mask RCNN are utilized to identify cotton plant leaf diseases [10].

1.3 Research gaps

By investigating previously established methods, this study seeks to implement a machine learning algorithm to recognize cotton plant leaf illnesses [10]. While conducting a literature review, the following research gaps are discovered:

- According to the literature, most plant disease identification is made for 5 to 10 diseases of various crops. However, they need to adequately satisfy even a single-crop disease study. Cotton plants are susceptible to 42 diseases. **This study**

reflects that most cotton plant leaf diseases kinds are identified utilizing deep learning technology and Transfer learning methodologies[11]. This might have a big impact on cotton agriculture and industry.

- Cotton leaf diseases have no standard picture dataset. **This study shows the creation of a cotton plant leaf disease dataset with 2800 data points. This helps produce better outcomes on real-time cotton plant leaf images. It could be a valuable contribution to the research community in this field.**

- Segmenting diseased portions in cotton plant leaves without plucking is a challenging task. There are certain diseases (like Whiteflies) whose pattern is changed if one plucks it, resulting in low accuracy in identifying diseases. **This study uses a CNN, Faster RCNN, SSD, and Mask RCNN algorithms to determine the health status of a plant leaf, the diseased portion on the plant leaf, and the type of disease (class)[12].**

- Previous research on plant disease and pest detection uses various techniques, including hyperspectral pictures and standard computer vision algorithms. Those technologies operate admirably in the settings tested. But the images and data required by the systems are difficult to collect. When dealing with real-time images of plant leaf diseases, their findings still suffer from high accuracy [13][8]. **This research demonstrates that 2800 real-time photos of diseased cotton plants are collected and tagged with disease names. The complete dataset is verified by Head (India), Quality Assurance, GOT, MAHYCO PVT. LTD. India.**

Chapter 2

Literature Review

The purpose of this chapter is to give some theoretical framework of the study. The literature review thus describes and analyses previous research on various topics like crop management, object detection plant leaf disease identification techniques. Machine Learning and Image Processing techniques have been used in the majority of the study. Plant nutrition is important in vineyard management since it influences factors such as fruit set, fruit quality, and ultimately the quality of the end output. Nutrition management in wine grapes and other crops is always varied and depends on a variety of elements such as soil type, weather, irrigation type, and so on [14]. There are two sorts of forces that might cause plant death and destruction: living (biotic) and nonliving (abiotic) agents. Insects, bacteria, fungi, and viruses are examples of living agents. Extremes of temperature, excess moisture, poor light, insufficient nutrients, poor soil pH, and air pollution are examples of nonliving agents. Plants that are sick can show a wide range of symptoms, making diagnosis challenging. Abnormal leaf growth, colour distortion, stunted development, and shrivelled are all common signs. Pests and diseases can result in significant yield reductions or plant mortality [15]. Many efforts have been taken into developing an automated approach or computer vision system for crop health monitoring. To recognise items in a digital image, many researchers integrate many other aspects such as color and texture with shape information. The color feature is used in various content-based image retrieval (CBIR) applications, such as morphological [16] and SVM [17] based. Color information was employed by Man et al. [17] for leaf recognition using a support vector machine (SVM). Similarly, compared to shape-based leaf image analysis, there is very little study on texture-based plant identification

systems. Texture characteristics are extracted using methods such as multi-scale fractal dimension [18], Gabor features [19], Relative Sub-image Coefficient (RSC) [20], Discrete Curvelet transform (DCT) [10], and other transforms. Prior to 2012, there is a lesser emphasis on identifying plant diseases. Using a whole isolated leaf image, multiple methods for plant species recognition are developed. These algorithms are divided into four categories: (1) algorithms based on leaf form [13][21][22][23][24][25][26], (2) algorithms based on leaf veins [27] [28] [29] (3) algorithms based on leaf margin [30] [31], and (4) algorithms based on leaf texture [18][19][20][10][32]. The majority of these are computationally expensive. White et al. [18] and Prasad et al. [33] uses a mobile device to compute and provide portability to such technology. However, there is very limited research on using digital image processing to detect plant leaf disease [34] [35] [36] [37] Automatically detecting plant leaf disease poses numerous challenges, but it will be a valuable tool for both researchers and farmers. S. Sankaran et al. [38] reviews advanced imaging techniques such as fluorescence spectroscopy, infrared spectroscopy, fluorescence imaging, hyperspectral imaging, and others. This approach can capture wavelength ranges that aren't apparent to the naked eye. According to the study, the techniques outlined can be connected with an autonomous agricultural vehicle for real-time crop monitoring, but they must be tailored to each type of plant. A. Meunkaewjinda et al. [39] finds a method for detecting two distinct illnesses in grapevines. The technology relies on color image processing and integrates a number of artificial intelligence algorithms to correctly divide plant tissue from the background and classify disease. The authors deals with an uncontrolled environment in which the background and illumination must be taken into account in order to obtain precise results. R. Radha et al. [40] proposes an algorithm to recognise veins and edges of leaves. Using healthy leaves, the programme produced correct findings. It generates binary masks that detect the veins and borders of the leaf so that a nutritional diagnosis may be performed later on the regions of interest. To diagnose the level of the leaf spot disease, a histogram-based method is proposed in [41] to separate the leaf from the background and the infected area from the leaf. The grayscale image or intensity image is used for segmentation. The classification technique is based on the relationship between the leaf area and the leaf affected area. G. Xu et al. [42] uses color pictures to identify tomatoes that are low in nitrogen and potassium. To prevent the effects of light and other environmental factors, the photos are taken with a sampling box. To separate the leaf from the background, histogram thresholding is applied. A color and texture study of

different samples of the same leaf allowed the deficit to be diagnosed 10 days before the experts could. A method for detecting lettuce calcium insufficiency is proposed in [43]. On real-time leaf photos, very little work is detected during the study. S Prasad et al. [44] proposed a method for closely monitoring and managing crop cultivation in India using mobile devices that may be used for real-time imaging as well as the identification of damaged plant leaves. The results of a dataset of 297 photographs taken with various mobile devices revealed that the higher the image resolution, the slower the processing. Many academics began using image processing techniques on real-time plant leaf photos after 2014 [44][45]. Deep learning techniques have recently been employed for object detection. Deep neural networks are being used in various domains to improve object detection accuracy. Object detection methods such as CNN, SSD, YOLO, RCNN, Faster RCNN, and Mask RCNN are commonly applied to increase accuracy [46][47][48][49][50][51].

Chapter 3

Objective of Thesis

Based on the research gaps studied, the following objectives are identified for the research study:

- To propose a technique for identifying the health status of Cotton plant leaves.
- To propose a methodology for identifying the disease-affected area of cotton plant leaves.
- To propose a methodology for the identification of the class of disease with improved accuracy.

Chapter 4

Research Contribution

This thesis proposes cotton plant leaves disease identification methods for targeting current issues such as less accuracy for real-time data. This study describes and justifies the data gathering and preprocessing method used for the analysis. It also outlines how different machine learning algorithms use these preprocessed data to get the expected results.

It is observed that cotton leaf is attacked by several diseases and insect pests, resulting in considerable losses in yield. Early diagnosis and recovery of these illnesses may aid in complete cotton crop development. Figure 4.1 demonstrates the generic framework for training and testing the deep learning meta-architecture for cotton plant leaf disease detection.

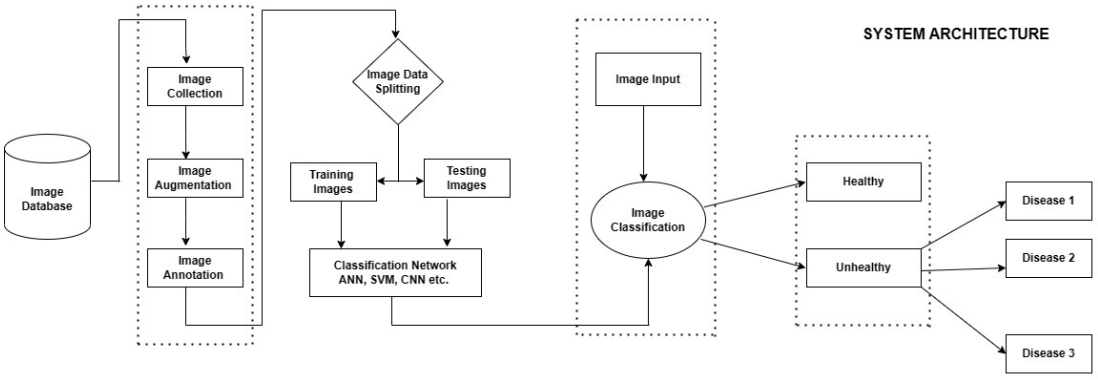


FIGURE 4.1: A generalized framework for training and testing a deep learning meta-architecture specifically designed for identifying diseases affecting cotton plant leaves..

4.1 A new image dataset for diseased cotton plant leaves:

A vital contribution to every Machine Learning (ML) model is preparing/acquiring the appropriate dataset. It aids in calculating the grip from such data and remembering the information for future predictions/detections. With training data, it is possible to train a system. Developing an accurate ML model requires ensuring that the correct and accurate data set is available. To achieve significant results in detecting plant diseases using Deep Learning techniques, incorporating additional data is often necessary[52]. Most currently available data sets are small, having less no of images of diseased leaves[13]. Also, no standard data set is available for cotton plant leaf diseases.

Observing the need, created a real-time image data set of diseased cotton leaves using the techniques below:

4.1.1 Data Collection

Created dataset with almost 2500-3000 data points because no standard real-time image data set is available for cotton plant leaf diseases. It will lead to the generation of better and more accurate results. Many nearby cotton fields are visited to capture the images. Five significant diseases fig. 4.2 are observed on cotton leaves in the Khandesh region of Maharashtra, notably.

1. Jassid Attack
2. Aphid Attack
3. Leaf Spot
4. Whiteflies
5. Magnesium Deficiency

Great care has been taken while capturing the cotton plant's diseased leaf images. Images captured are from various perspectives and contrasts to obtain a diverse dataset. Extra care is taken, as plucking the leaf may contaminate the afflicted area.

FIGURE 4.2: Real time Cotton plant leaf disease images .

A 48 MP ISOCELL Brilliant GM2 sensor camera from Samsung was utilized to create the picture data collection. It sports a 1/2.25" sensor with 0.8µm pixels and an aperture of f/1.8. When native pixel-binning is used, the picture output is 12MP. The 8MP sensor with an f/2.2 aperture powers the 119-degree ultrawide-angle camera. It is a 2MP macro camera (sensor pixels are fairly huge, 1.75m).

4.1.2 Data preparation

All the images are correctly examined and separated from the hazy images. Some of the photos were not having a disease portion. The complete filtered set of collected photos is sent to an expert botanist (Head India, Quality Assurance, GOT, MAHYCO PVT. LTD. India) who confirms the diseases and provides insight into the dataset. The entire data set is labeled and annotated to prepare the Machine Learning model and for training.

4.1.3 Data annotation

Image annotation is the process of labeling or classifying photographs with annotation tools to identify data objects with machine learning models. The most common uses of image annotation are distinguishing between objects and boundaries and segmenting images. In this instance, the annotation instrument is "labelImg." LabelImg is a user-friendly, open-source tool that enables the visual annotation of images. The graphical user interface of this software application is developed using QT, and the underlying

code is implemented in Python. LabelImg can process and interpret two types of labeling file formats, namely VOC XML and YOLO text files. When detecting objects, the VOC XML standard is more prevalent. All annotations in this data set are stored in VOC XML format. Each image is appropriately labeled. Each diseased region in the image has been assigned a precise bounding box, as seen in fig. 4.3, which is subsequently labeled. The essential aspect of labeling is that the names of classes (diseases) should not be confused. After labeling the images, it is observed that the Jassid Attack disease class has fewer data points than other classes. Such data inconsistency within the dataset could be disastrous for the machine learning model.

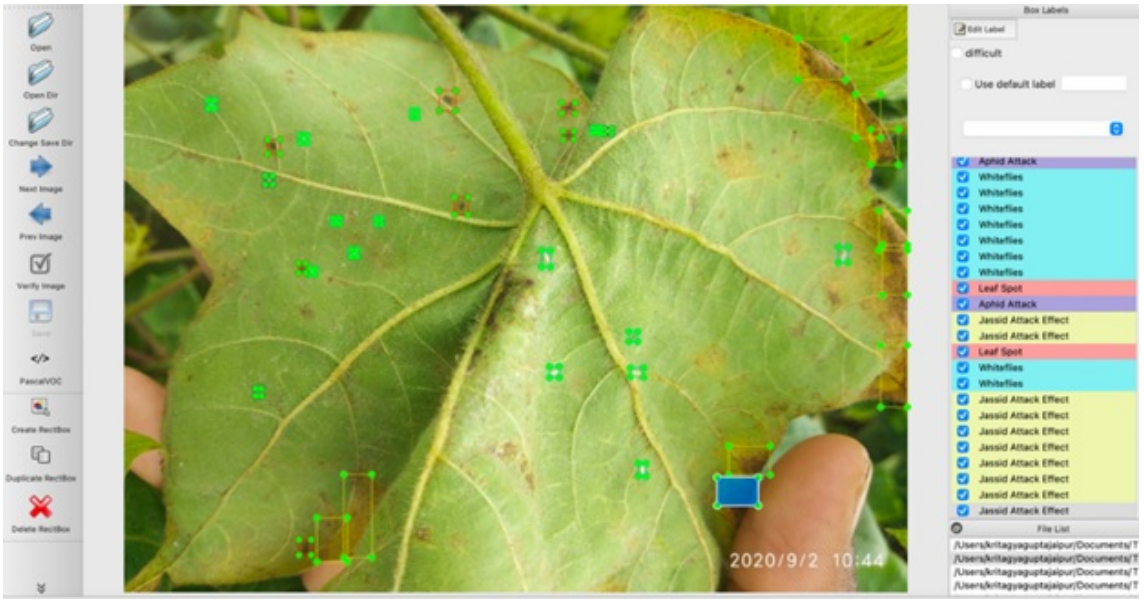


FIGURE 4.3: Annotations using LabelImg .

4.1.4 Data augmentation

Image augmentation is an effective method if there is insufficient data to train the deep learning model. Picture augmentation is a technique for changing existing photos to provide more data for model training. In other words, it is a strategy for artificially boosting the dataset available for deep learning model training. As previously stated, the number of data points in Jassid attack classes must be raised to balance the dataset. So, data augmentation was performed on the Jassid Attack class. Python script is written for this purpose. The program is created to generate eleven augmented images for input images. This script only works with VOC XML. An image augmentation library

(Imgaug) and a library used to create image annotation XML files in the PASCAL VOC file format (Pascal voc writer) are imported. Apart from it, Glob is included, which returns all file paths that match a given pattern so that there is no need to pass a single image at a time. It will accept an entire image directory.

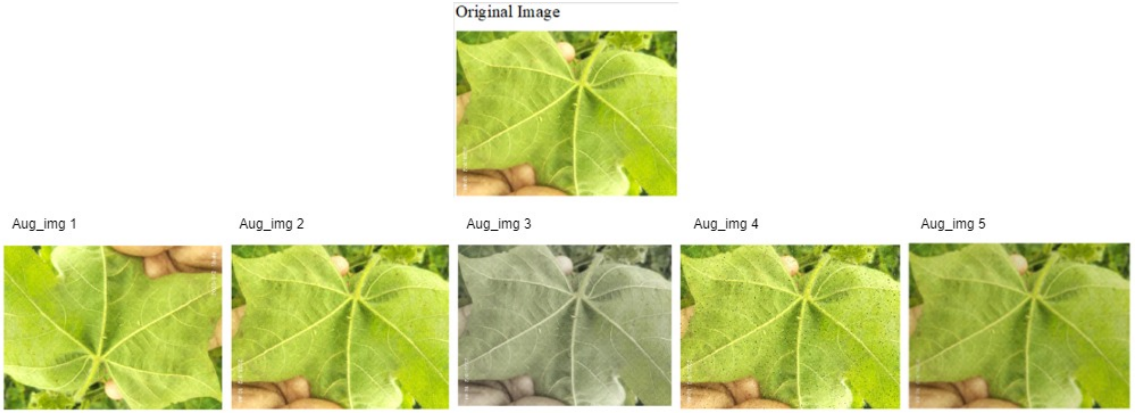


FIGURE 4.4: Data Augmentation .

The program takes an input image and alters its contrast, brightness, zoom, crop, rotate, and other properties to produce various images. The code comprises a for loop that iterates the same process for each image in the input directory, and the result files are initially stored in an empty output directory. Augmentation is performed on tagged photos to save time. The method duplicates the annotations from the original image (input image) to all the output images (augmented images), eliminating the need to label those images twice fig. 4.4.

4.2 A technique for identification of the health status of Cotton plant leaves using Convolution Neural Network (CNN):

A deep convolution neural network is also referred as a deep feed-forward artificial neural network (DCNN). This approach is frequently used in various industries for item detection[53]. Various studies show this approach is quicker than other classification

methods. This research uses a Convolution Neural Network (CNN) to identify the unhealthy parts in images of cotton plants. The results demonstrate that the model distinguishes between healthy and ill cotton leaves. Plant photographs are used as input to the convolution neural network. Unhealthy plant images contain qualities that distinguish them from healthy plant images. These characteristics include patterns, colors, disease states, plant locations, and so on. The image's color or pattern information influences the neurons' activity in CNN[3]. These characteristics have been studied to discover whether plant leaves are diseased.

4.2.1 Performance evaluation

4.2.1.1 Comparative accuracy analysis with CNN

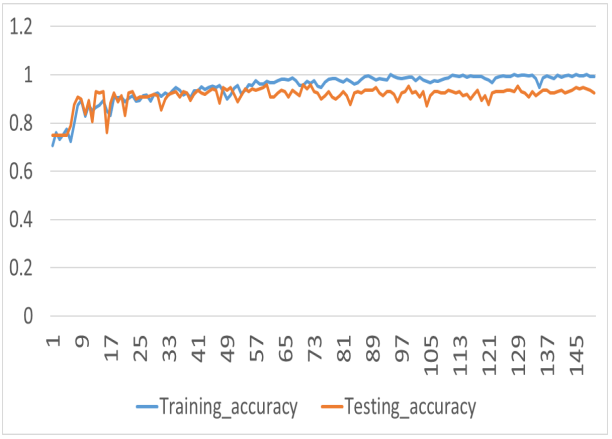


FIGURE 4.5: Training and Testing Accuracy.

The training and testing data were visualized using graphs to understand how the CNN model worked. With the use of data gathered during each training and testing phase, a graph was produced to compare the accuracy of training and testing. Fig. 4.5 can be seen with the same comparison. This graph contains accuracy data for each of the 150 epochs. By studying this graph, it can be observed that CNN works much more efficiently in learning and works accurately in testing.

Similarly, fig. 4.6 and fig. 4.7 are graphs plotted for training and testing accuracies and losses. This graphs helps to determine at which epochs the model is learning at higher rate and at what point the model having losses. Loss is the penalty for wrong

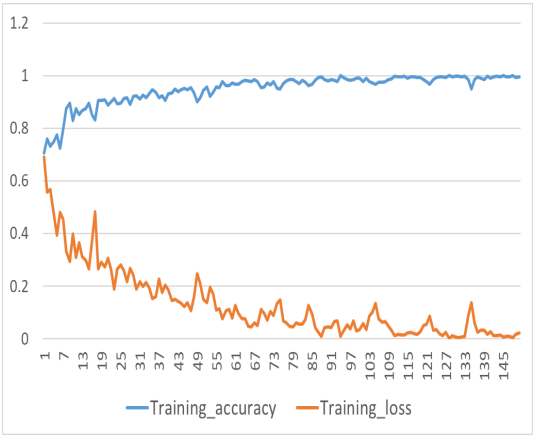
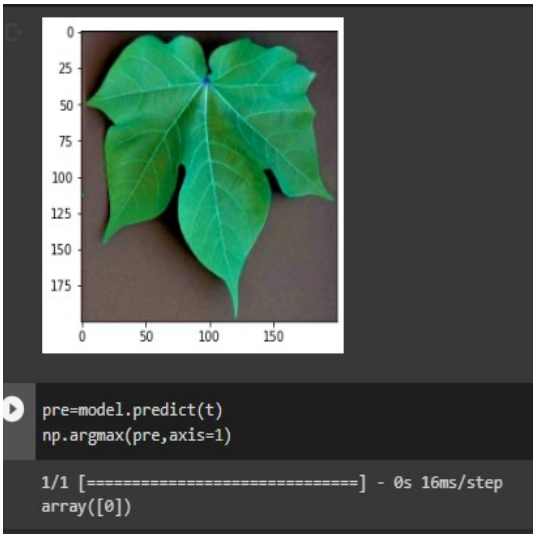


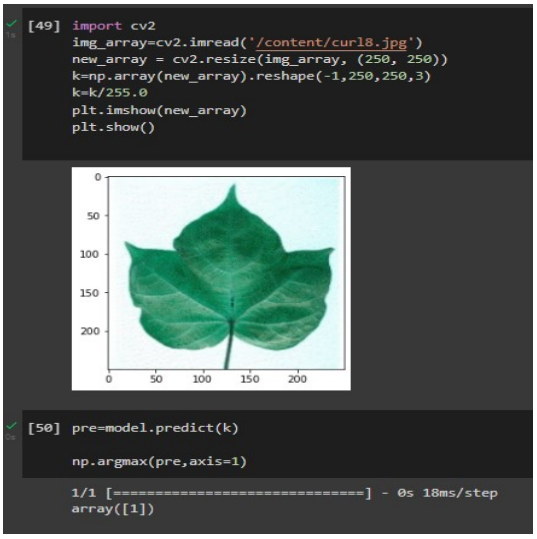
FIGURE 4.6: Training Accuracy and Training Loss.

FIGURE 4.7: Testing Accuracy and Testing Loss.

predictions. So, with help of this graphs we can build the models more precisely and eradicate any scope of error.



(A) Healthy.



(B) Unhealthy.

FIGURE 4.8: Predictions of CNN Model.

Figure 4.8 shows the predictions of CNN model when tested for testing data. Class 0 represents a healthy plant leaf while 1 represents unhealthy plant leaf.

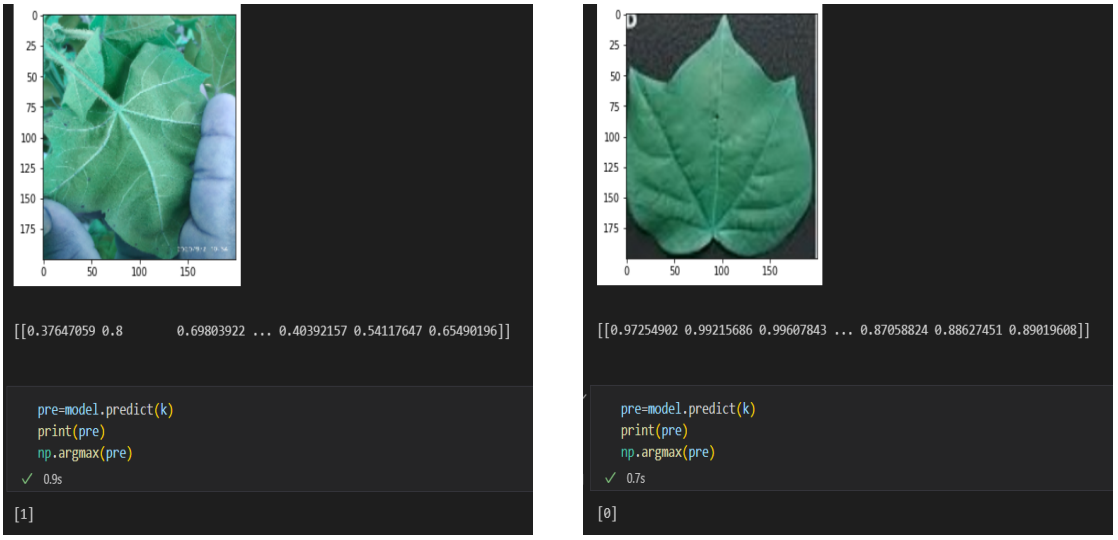
4.2.1.2 Comparative accuracy analysis with SVM

Table 4.1 gives the classification report of the SVM model. This classification report is useful for understanding model learning. Here. 0 and 1 are the two classes for which

	Precision	Recall	F1-score	Support
0	0.77	0.81	0.79	129
1	0.94	0.92	0.93	383
Accuracy			0.89	512
Macro Average	0.85	0.87	0.86	512
Weighted Average	0.89	0.89	0.89	512

TABLE 4.1: Classification report of SVM model

predictions were made. '0' stands for Healthy class, while '1' stand for Unhealthy. The accuracy, recall, f1-score, and support values for the various performance assessment measures are provided in this report. The algorithm reached an accuracy of 89



(A) Healthy. (B) Unhealthy.

FIGURE 4.9: Predictions of SVM Model.

Testing for predictions was done using a testing dataset, and it was found that SVM could predict Healthy and Unhealthy classes. Fig. 3.12(A) shows the prediction of Class 0, i.e., Healthy, and Fig. 3.12(B) contains the results for classifying Class 1, i.e., Unhealthy.

4.2.1.3 Comparative accuracy analysis with ANN

The graphs for training and testing accuracies corresponding with their losses were plotted. The same can be seen in Figure 4.6. When comparing these graphs with graphs

(fig. 4.10 and Fig. 4.11) of CNN, it can be concluded that CNN was found to be more efficient in both training as well as testing.

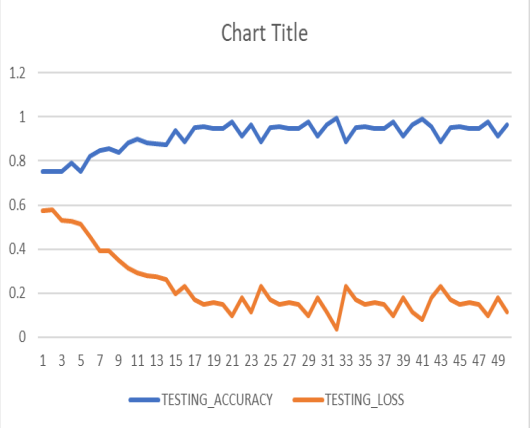


FIGURE 4.10: Training Accuracy and Testing Accuracy Loss.

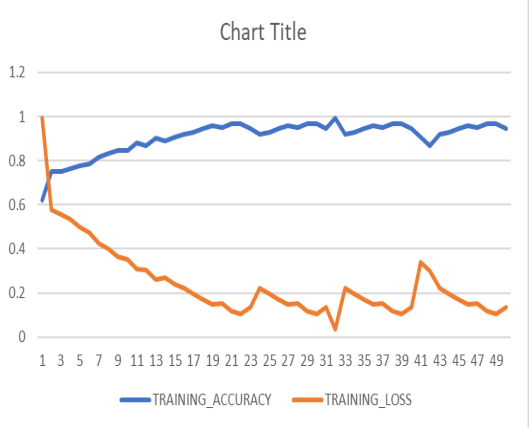
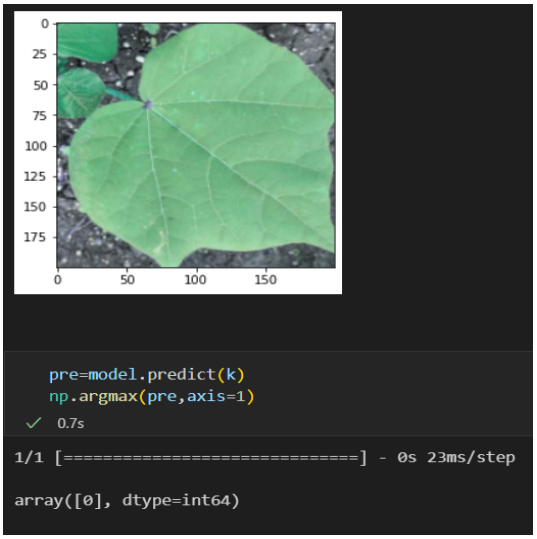
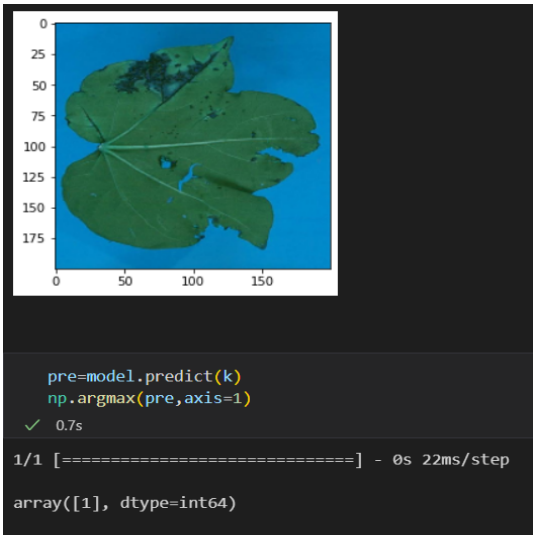


FIGURE 4.11: Training Accuracy and Training Loss.

As seen in, Fig. 4.12, the accurate prediction of both classes 0 and 1, which represent the Healthy and Unhealthy classes, respectively.



(A) Healthy.



(B) Unhealthy.

FIGURE 4.12: Predictions of ANN Model.

4.2.1.4 Parametric description of Machine Learning Models

The Adam optimizer is chosen, as indicated in Table 4.2, because it is an adaptive gradient descent optimization approach that determines appropriate learning rates for

Dataset	Model	Images	Epoch	Activation Function	Optimizer	Loss Function	Image Size	Accuracy
Dataset 1	**CNN**	1811	150	ReLu, Tanh, Sigmoid	Adam	Sparse Categorical Cross-entrophy	200x200	96.25
	ANN	1811	50	ReLu, Sigmoid	Adam	Sparse Categorical Cross-entrophy	200x200	95.47
	SVM	1811	30	-	Adam	Hinge	200x200	89.06
Dataset 2	**CNN**	2987	150	ReLu, Tanh, Softmax	Adam	Sparse Categorical Cross-entrophy	250x250	94.68
	ANN	2987	80	ReLu, Softmax	Adam	Sparse Categorical Cross-entrophy	250x250	90.57
	SVM	2987	50	-	Adam	Multi-Class SVM Loss	250x250	89.87

TABLE 4.2: Parametric Accuracy on different ML Models

different parameters using estimates of the gradient's first and second moments. Using this approach, the optimizer can converge more rapidly and effectively than standard gradient descent methods. The Adam optimizer is well-liked because of a variety of benefits. It has been recommended as the default optimization strategy and has been used as a benchmark for deep-learning papers. Furthermore, compared to other optimization techniques, the approach is simpler to build, runs faster, uses less memory, and needs less tuning. The Adam optimizer combines the best aspects of all algorithms, making it the best optimizer currently available.

Used relu because It is a simple and efficient activation function that overcomes some of the limitations of other activation functions, such as the vanishing gradient problem.

ReLu is computationally efficient and allows neural networks to converge faster and perform better in many applications.

Tanh was used as Tanh, like a sigmoid, to activate the output layer for binary classification. It features a non-zero-centered gradient, which might assist in mitigating the vanishing gradient issue in deep neural networks. All of an image's features are utilized for training. The tanh function may assist the model in learning more complicated correlations between features, which is very effective in the image and voice recognition applications.

Softmax should be utilized as the last layer's output function in neural networks (if the network has n layers, the softmax function is the n-th layer). It is crucial since the last layer aims to translate the neural network's score into human-interpretable values.

SVM employs a hinge loss, which conceptually emphasizes the boundaries. As a result of the function's "hinge" (the maximum), points further away than the closest contribute nothing to the loss. These nearest positions are merely the support vectors.

Sparse Categorical Cross-entropy is an optimization method used to reduce loss in tasks that require classifying many attributes or labels for each input example, such as multi-label classification tasks.

The image size of our dataset ranges from 100X100 to 300X300 to get an optimal resolution for all images, we have kept 200X200 size for all images.

The Adam optimizer is an adaptive gradient descent optimization method that determines individual learning rates for different parameters using first and second-moment estimates for the gradient. It has been recommended as the default optimization strategy and has been used as a benchmark for deep-learning papers. Relu is a straightforward and effective activation function that gets around issues with other activation functions, such as the vanishing gradient issue. Softmax and parse should be utilized in neural networks as the last layer's output functions. An optimization method called categorical cross-entropy is used to reduce loss in multi-label classification problems. The image size of our dataset ranges from 100X100 to 300X300. To get an optimal resolution for all images, the size was kept to 200X200.

4.3 Single Shot Detector (SSD) and Faster RCNN to recognize the disease-affected area of cotton plant leaves:

This research advances our understanding of how to use transfer learning to identify plant illnesses. The study's performance examination of three different algorithms highlights the benefits and drawbacks of each tactic. SSD-Mobile Net appears to be a viable algorithm for this purpose, as it is lightweight and quick, making it suited for deployment on mobile devices.

SSD-VGG16, on the other hand, is more accurate but slower and heavier, making it better suited for deployment on high-end servers or workstations. It might be useful for high-precision applications such as disease detection in high-value crops.

Furthermore, our results show that Faster R-CNN-VGG16 performed better in accuracy than SSD-VGG16 and SSD-Mobile Net, achieving an accuracy score of 85.01. Because it was the slowest and heaviest of the three algorithms, it was less suitable for mobile devices or low-power systems.

Overall, the study's findings emphasise the importance of selecting the right algorithm for the application's demands and specifications. Our findings have substantial implications for academics and practitioners working on computer vision applications in general, as well as those developing plant disease monitoring systems. By utilising the benefits of transfer learning and carefully considering variables like as speed, accuracy, and deployment platform, one may design effective and efficient disease detection systems that can boost agricultural output and reduce the need for pesticides.

4.3.1 Performance evaluation

TABLE 4.3: Experimental results on Cotton plant disease

Algorithm	Model Results
SSD-VGG16	81.23
FasterR-CNN-VGG16	85.01

The results reported in the table 4.3 show the performance of each algorithm on a particular dataset, where the metric used for evaluation is not mentioned. However, it is

assumed that the reported numbers represent the average precision (AP) metric, which is commonly used for evaluating object detection models.

The SSD-VGG16 algorithm achieved a result of 81.23% on the dataset, while the Faster R-CNN-VGG16 algorithm achieved a higher result of 85.01%.

As a result of having a higher average accuracy score than the SSDVGG16 model, the Faster R-CNN-VGG16 model is better at identifying objects in the test dataset.

4.3.1.1 Results for SSD-VGG16

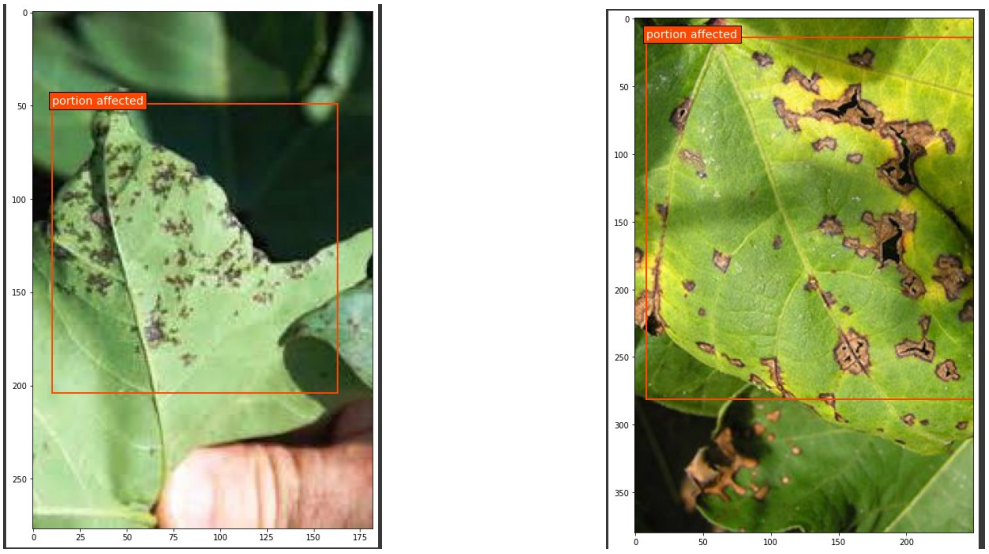


FIGURE 4.13: Results for SSD-VGG16.

This is the prediction made by SSD-VGG16 model shown in fig. 4.13 where the Ground truth value was provided to the model and given a UoI threshold of 0.5, resulting in the above images.

As shown if fig. 4.14 Loss over epochs is decreasing, and validation loss is also decreasing. This shows that our model is learning to detect the diseased portion effectively and accurately.

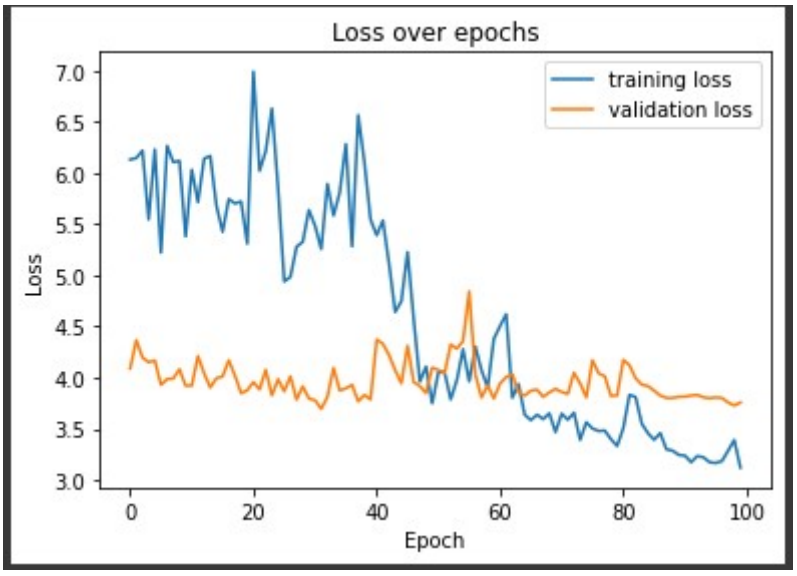


FIGURE 4.14: Loss graph for SSD-VGG16.

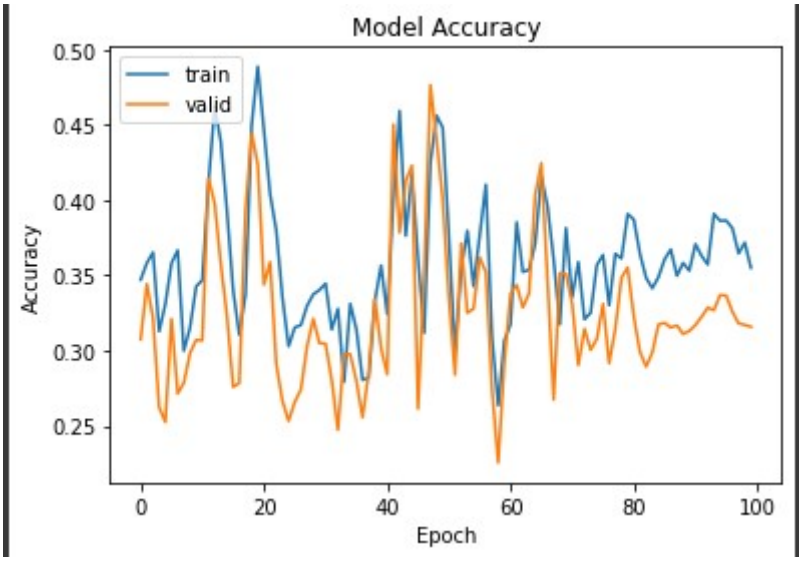


FIGURE 4.15: Accuracy Graph for SSD-VGG16.

In the above Graph 4.15, we can see that model .is able to predict the diseased portion accurately.

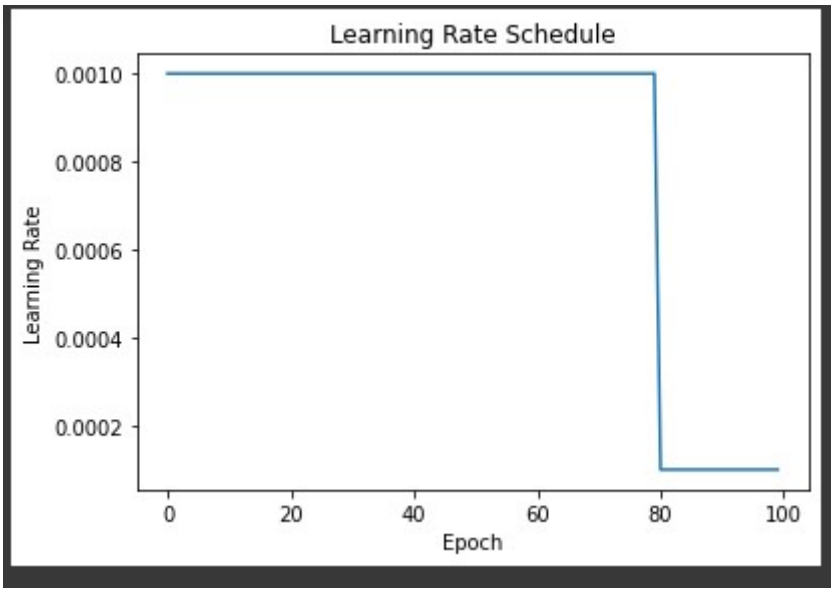


FIGURE 4.16: Change in Learning Rate.

In the Graph 4.16, we can see at 80 epochs, our learning rate changes so that the model can learn where the object is efficient.

4.3.1.2 Results for Faster R-CNN

The Length of each Epoch for training is 100. The number of epochs trained here is 24. Every epoch spends around 450 seconds, equaling the total training time of 3 hours. These are a few Results obtained while training our model. As shown in fig 4.17 the green box represents the ground truth box, while the purple box represents the anchor, which is calculated by the RPN layer.

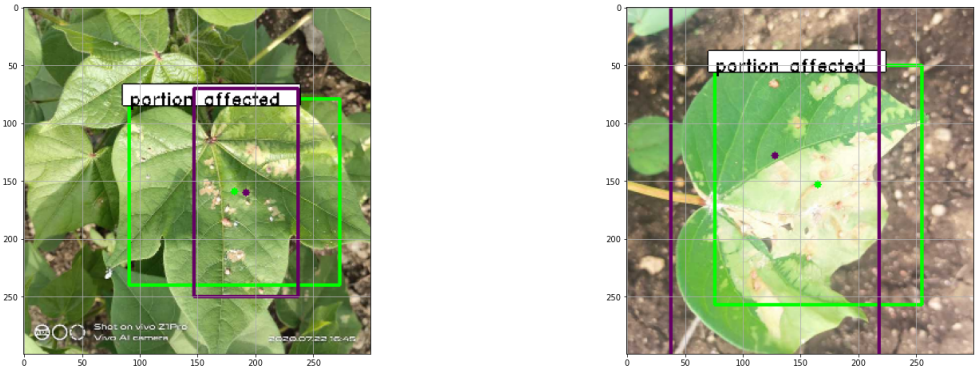


FIGURE 4.17: Training Images for Faster RCNN.

The loss function converts the mistakes into a numerical value to determine how significant the object detector's mistakes are.Two loss functions are applied to both the classification model and the regression model. The regression model has two losses: 1) It is used to classify whether an object is present, 2) The other is used to identify bounding boxes coordinates

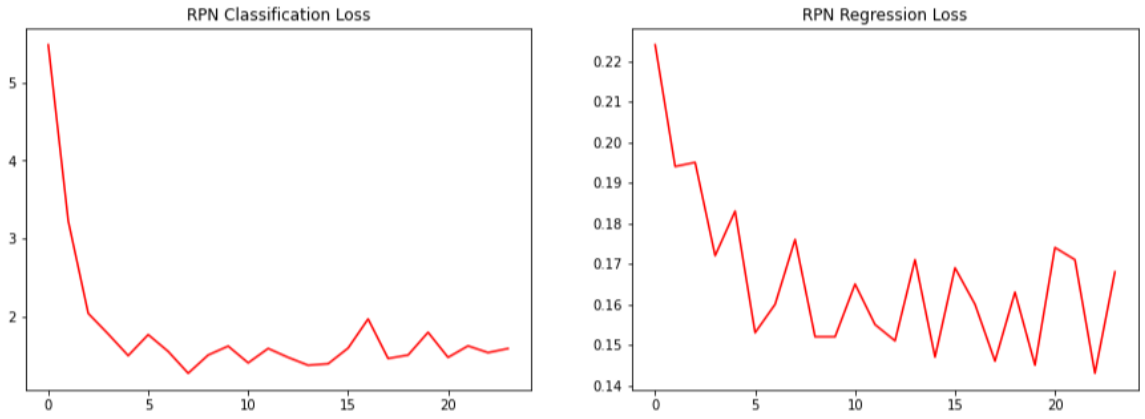


FIGURE 4.18: RPN Model Losses.

Similarly, for the classifier layer, two loss functions have been applied. We can see from the image above that it was able to learn very quickly during the first five epochs. Objectness accuracy is already great at this early stage of our training, but the precision of bounding box coordinates is still low and needs more time to learn.

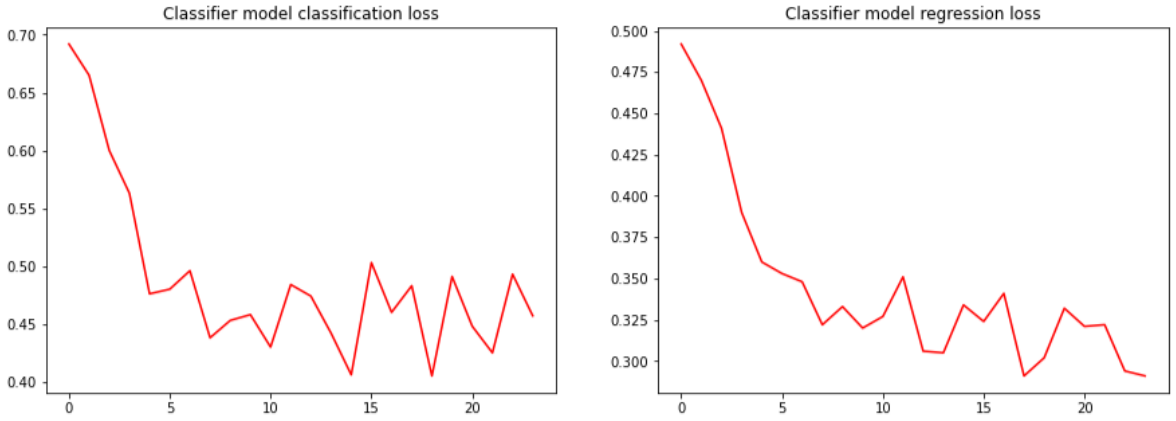


FIGURE 4.19: Classifier Model Losses.

FIGURE 4.20: Total Training loss.

It is the total training loss of the model. It is the addition of all four losses shown in fig. 4.18 and fig. 4.19. It keeps on decreasing as the number of epochs increases. It decreases drastically till the 5th epoch gets trained. The total loss after training 24 epochs is 2.5 shown in graph 4.20.

4.3.1.3 Comparative analysis with mobilenetv2 as Backbone

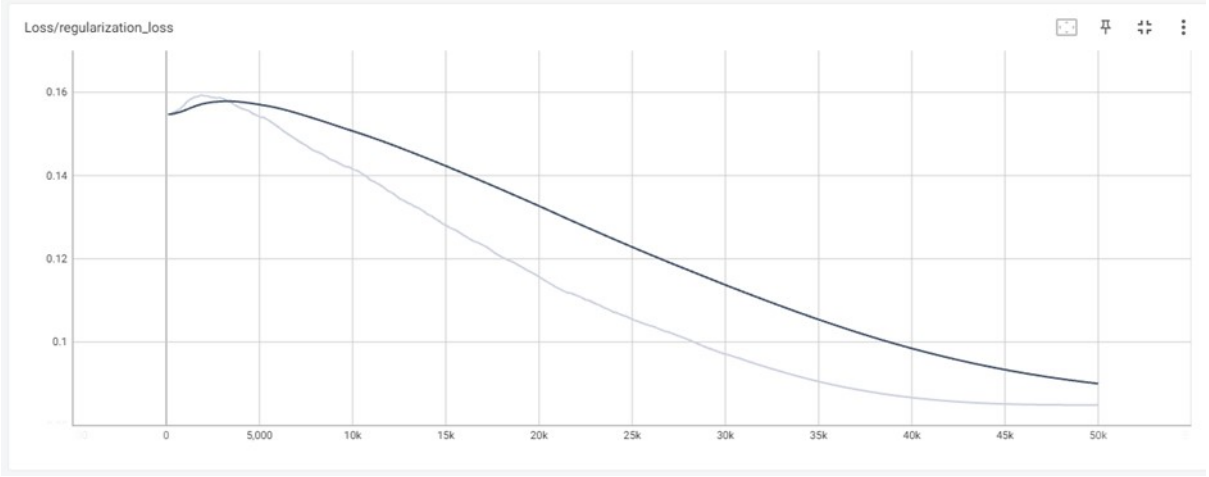


FIGURE 4.21: Loss Graph Regularisation for SSD-MobileNet.

In 4.21 graph, we can see regularisation loss decreasing over every iteration, preventing overfitting so that our model can Generalize.

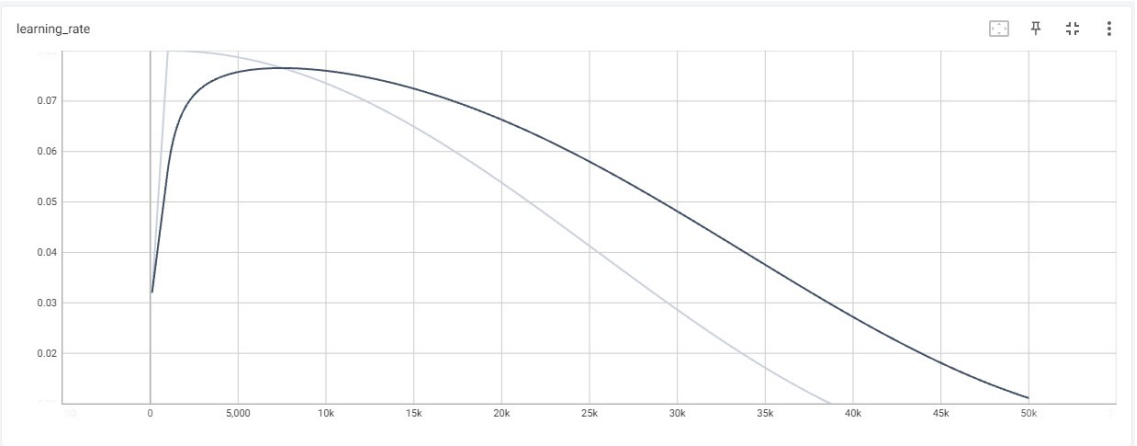


FIGURE 4.22: Learning rate graph for SSD-MobileNet.

In 4.22 Graph, we can see at 80 epoch our learning rate changes so that over model can learn where the object is efficiently.

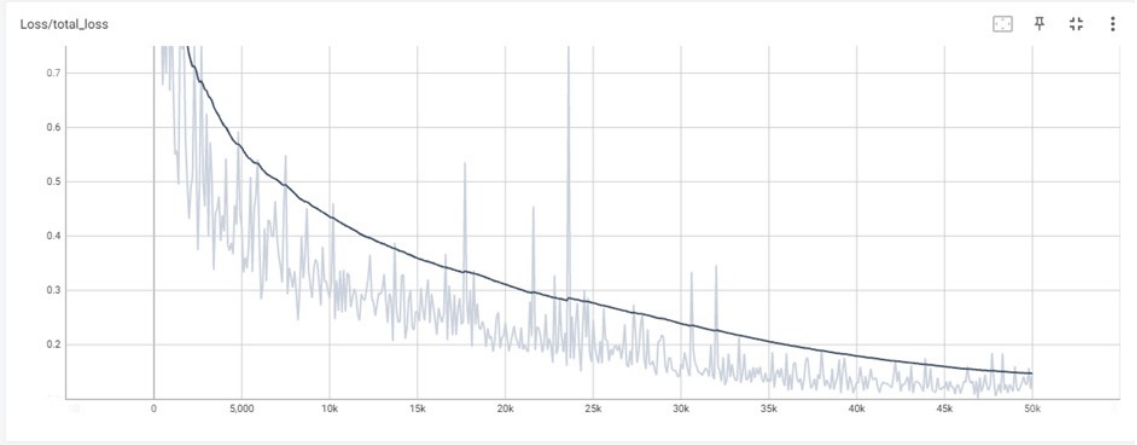


FIGURE 4.23: Total Loss graph for SSD-MobileNet.

So, in 4.23 graph total loss decreases over every iteration, which helps the model to detect diseased portion effectively.

In figure 4.24, we can see that in every Epoch, Localisation Graph is Decreasing, indicating that the model can locate objects easily with every passing Iteration.

These predictions are made by SSD-Mobilenet.

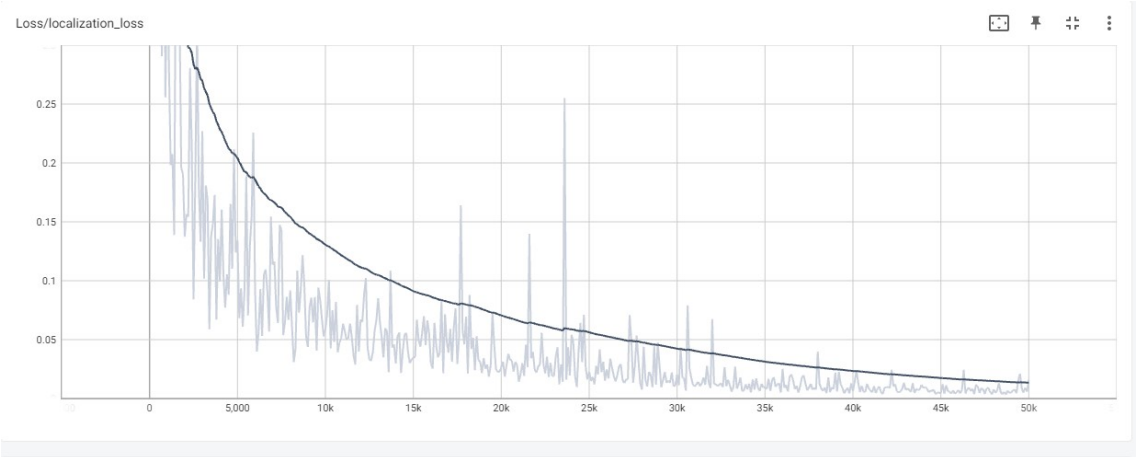


FIGURE 4.24: Localisation graph for SSD-Moblenet.

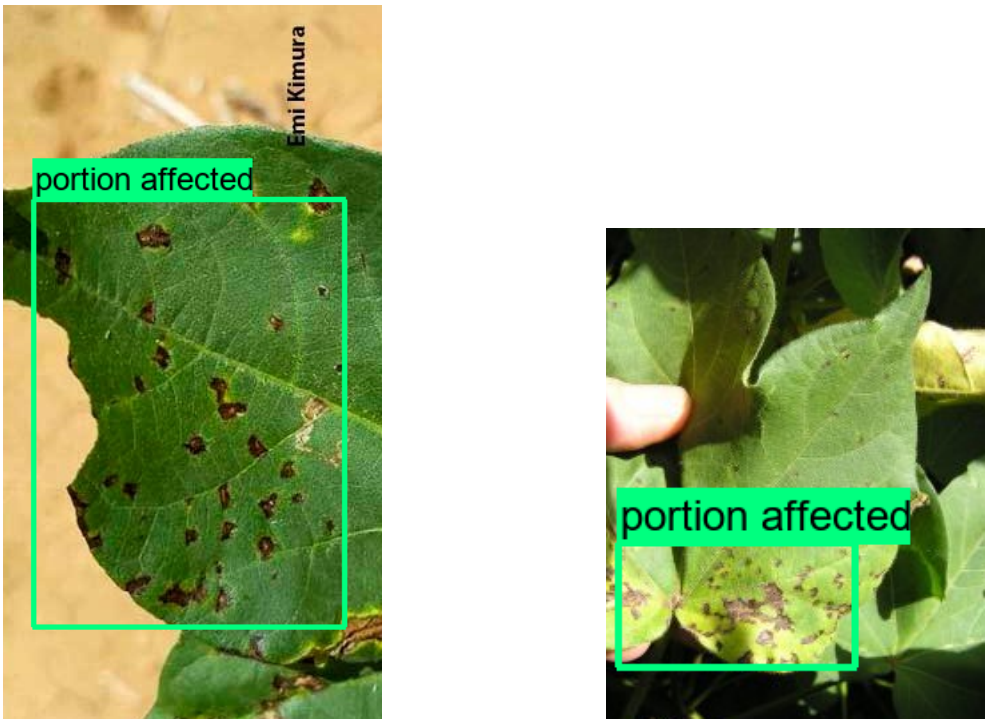


FIGURE 4.25: Results with SSD VGG-16.

4.3.1.4 Comparative analysis with VGG16 and Mobilenet

Architecture: While SSD-MobileNet employs the MobileNet architecture as its foundation network, SSD-Vgg16 uses the VGG16 architecture. While MobileNet is a thin and effective architecture built for mobile devices, VGG16 is a deeper and heavier architecture.

Speed: Due to the reduced size and fewer parameters of the MobileNet design, SSD-MobileNet is quicker than SSD-Vgg16. Because of this, it is perfect for real-time object identification applications, especially on mobile devices with little processing power.

Accuracy: Because of the deeper and more intricate design, cotton is typically more accurate than SSD-MobileNet, as seen in table 4.4. However, the accuracy gap is small and may be reduced by applying additional strategies like data augmentation and fine-tuning.

TABLE 4.4: Experimental results on Cotton plant disease

Algorithm	Model Results
SSD-VGG16	81.23
SSD-Mobilenet	78.09
FasterR-CNN-VGG16	85.01

Deployment: SSD-MobileNet is more suitable for deployment on mobile devices due to its smaller size and faster speed. On the other hand, SSD-Vgg16 is more suitable for deployment on high-end servers or desktops. The result are shown in figure 4.25.

4.4 Mask Region-Based Convolutional Neural Networks (Mask RCNN) methodology for identifying the exact disease name and improving accuracy obtained using Single Shot Detector (SSD) algorithm:

SSD algorithm determines the location and name of leaf maladies on cotton plants. The results demonstrate that it correctly identifies disorders, but the algorithm's precision could be better. Mask RCNN can be used for more precise object detection, according to additional research. Image segmentation is the technique used in computer vision to divide a digital image into numerous sections (pixel sets, also called image objects)[54]. This segmentation is employed to identify objects and boundaries (lines, curves, etc.). Instance segmentation is concerned with correctly detecting all objects in an image and segmenting each instance precisely. In contrast, Mask RCNN semantic segmentation means identifying or classifying similar items as a single class at the pixel level. The

findings indicate that the instance segmentation model is used to detect disease in cotton plant leaves.

4.4.1 Performance evaluation

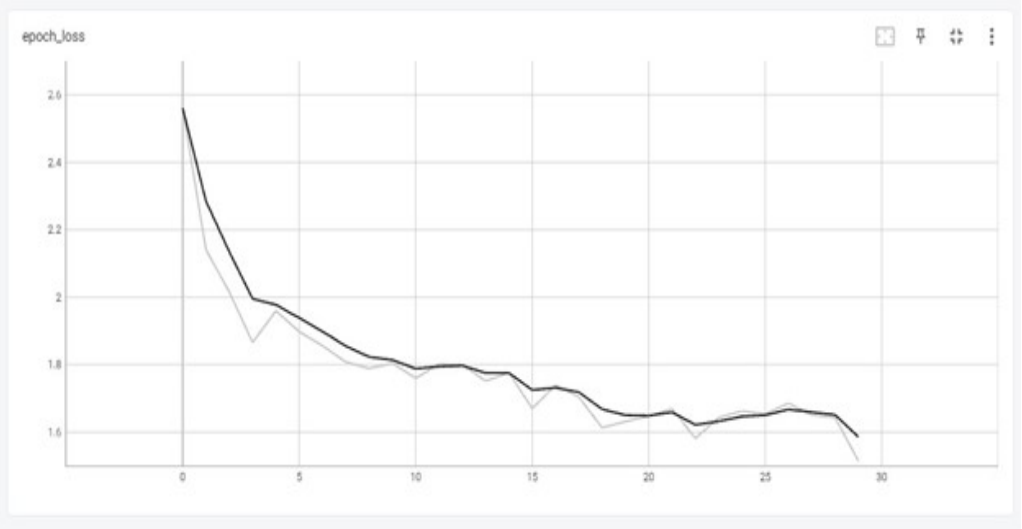


FIGURE 4.26: Epoch vs Loss.

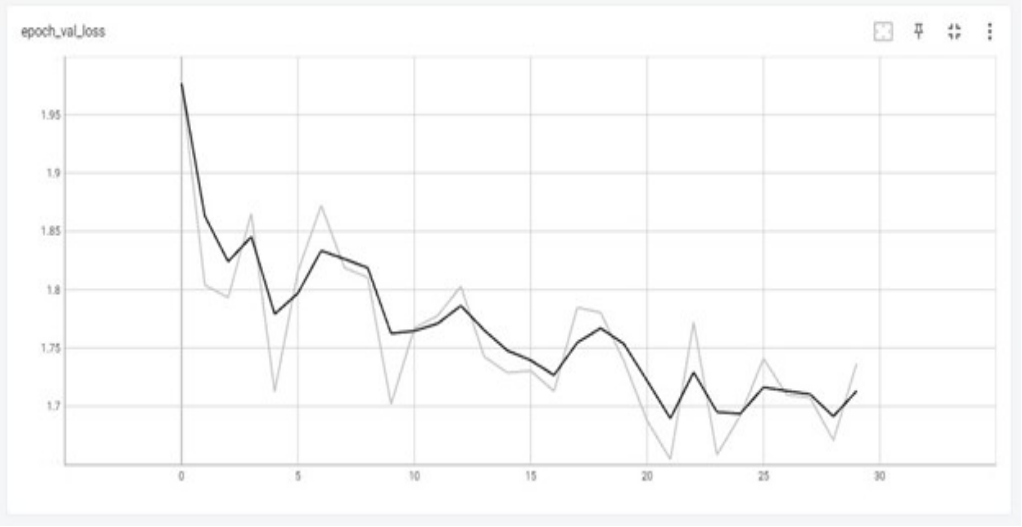


FIGURE 4.27: Epoch vs Validation Loss.

The epoch loss graph is a helpful visualization tool that can be utilized to monitor the performance of the Mask R-CNN algorithm. At the same time, it is being trained and locating regions that could benefit from improvement. The preceding graph provides evidence to support the claim that losses get smaller as the number of epochs increases up to a certain point shown in fig. 4.26 fig. 4.27.

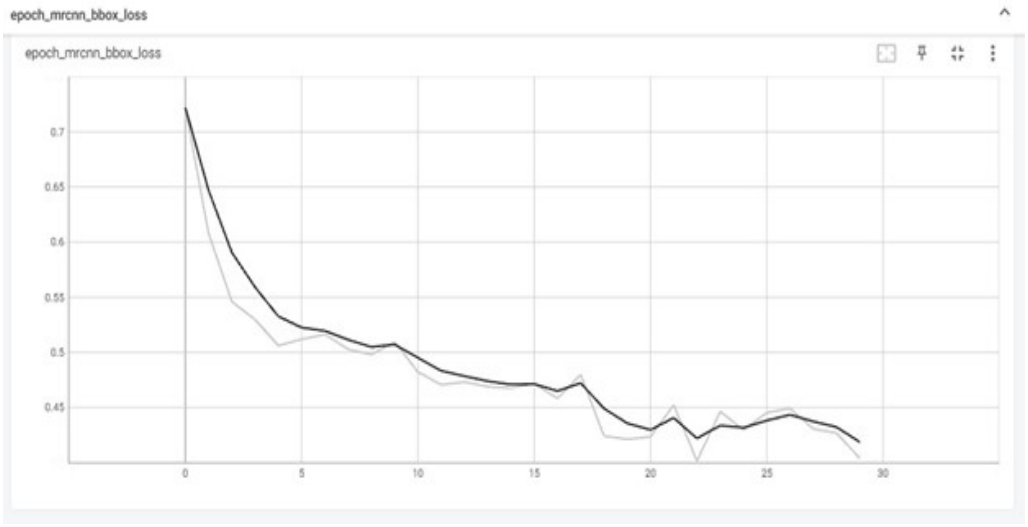


FIGURE 4.28: Epoch vs Bounding Box Loss.

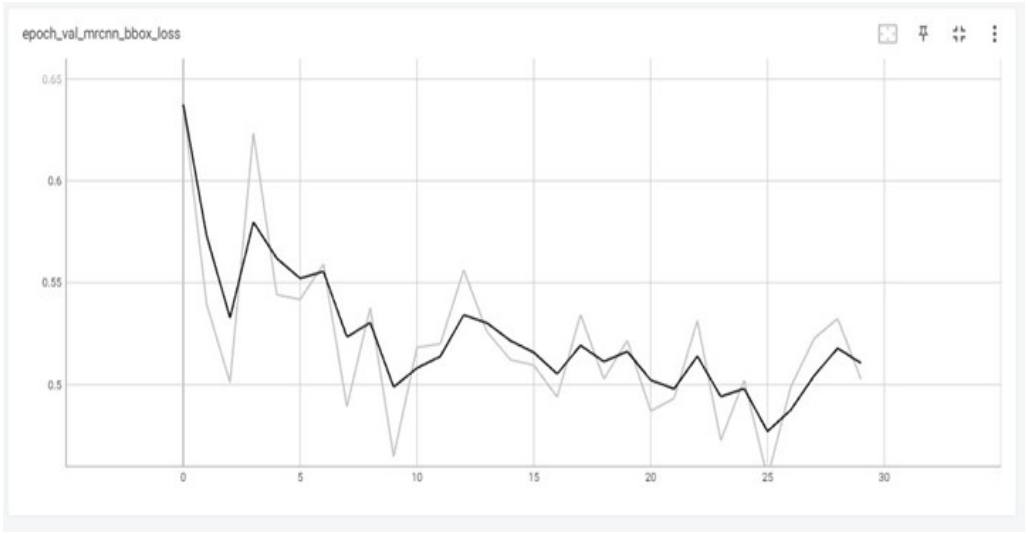


FIGURE 4.29: Epoch vs Validation Bounding Box Loss.

The bounding box loss plotted against the epoch is shown in fig. 4.28 fig. 4.29. The bounding box loss measures the model's ability to accurately anticipate the bounding box coordinates surrounding each item in the picture. The bounding box coordinates are better predicted with time by the model, as seen by a declining trend in the epoch mrcnn-box-loss graph.

The RPN bounding box loss for each item proposal aims to minimize the discrepancy between the predicted and actual bounding boxes. The epoch RPN bbox loss graph has a decreasing trend, which suggests that with time, the RPN is improving its ability to predict the coordinates of the bounding boxes for the suggested objects fig. 4.30 fig.

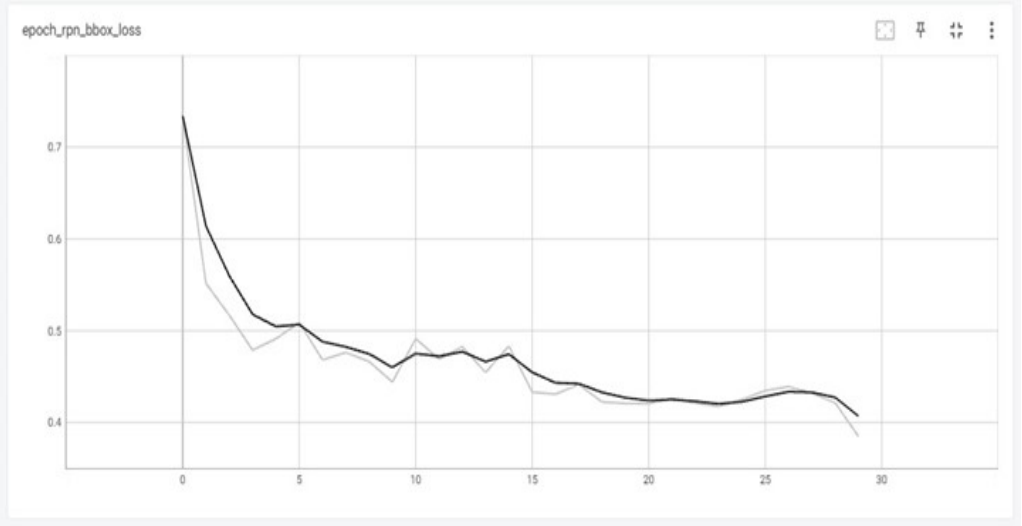


FIGURE 4.30: Epoch vs Bounding Box Loss.

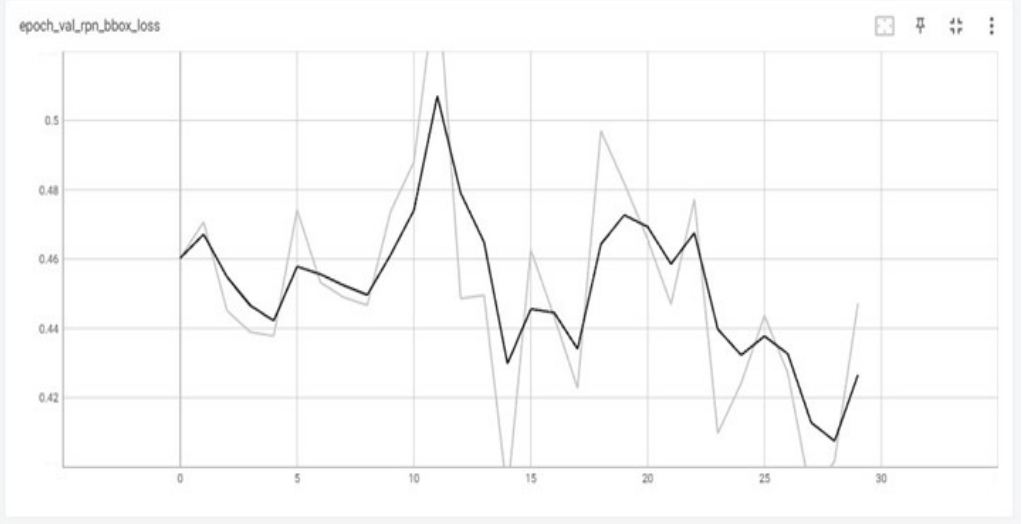


FIGURE 4.31: Epoch vs Validation Bounding Box Loss.

4.31.

The above image is the result of the proposed model successfully being able to classify disease and identify the portion infected because of the disease.

Similarly, the images fig 4.32 fig. 4.33 fig. 4.34 are also part of the testing. The model identified and detected segments/portions of leaf infected and disease-causing these adverse effects. Leaf spots, white flies, and jassid attacks are some of the diseases the proposed model identified.

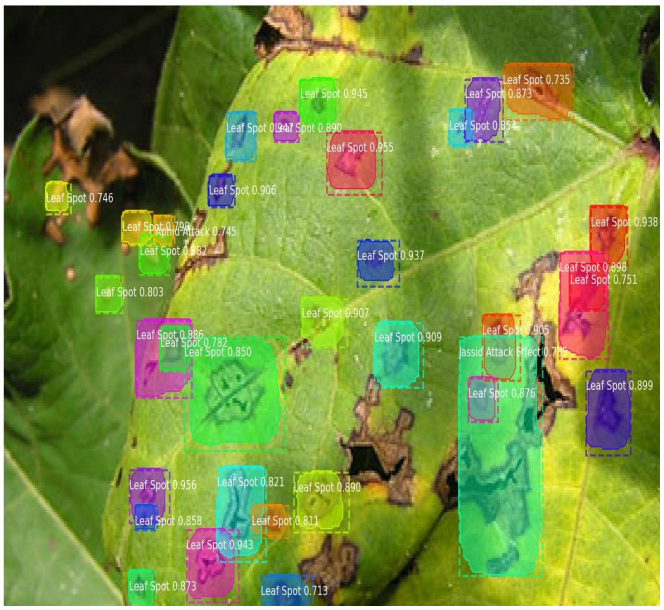


FIGURE 4.32: (a) Mask RCNN result of Multi-Class disease.

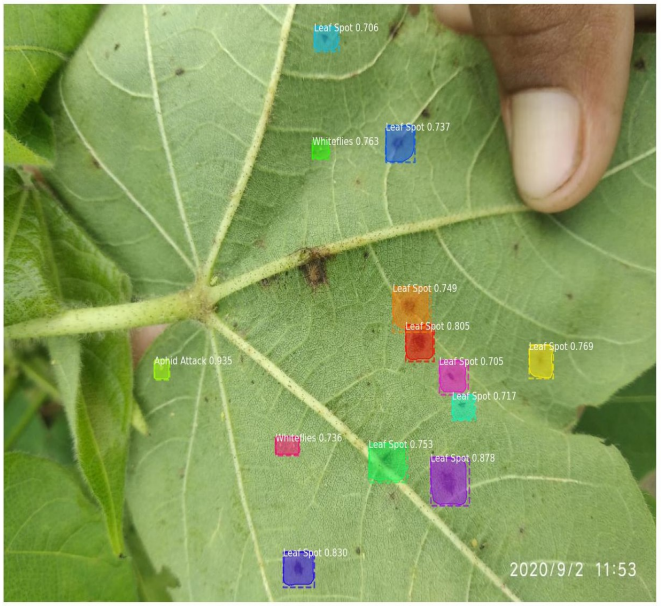


FIGURE 4.33: (b) Mask RCNN result of Multi-Class disease.

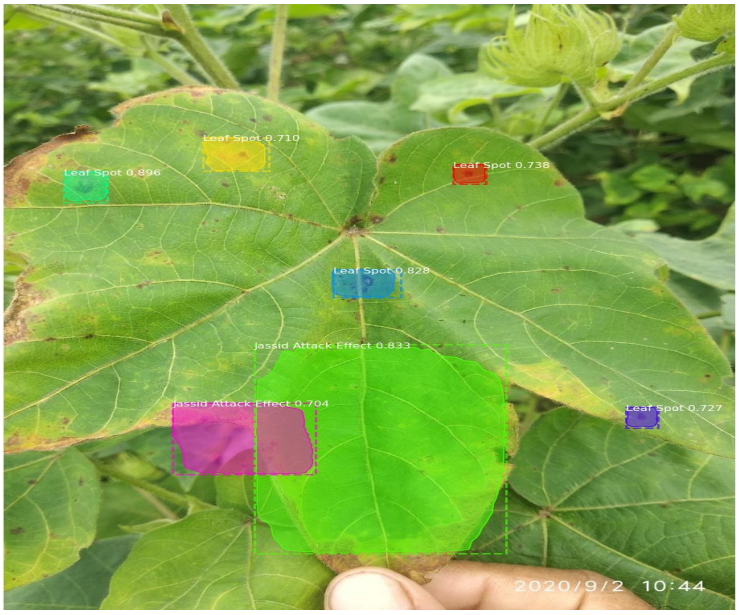


FIGURE 4.34: (c) Mask RCNN result of Multi-Class disease.

Chapter 5

Conclusions

This chapter addresses how the objectives have been achieved and the results obtained by applying the different Machine learning algorithms on cotton plant leaf disease dataset.

In this study, a comparative analysis of various machine-learning techniques for detecting cotton plant diseases using leaf images is done. Like humans, plants are susceptible to several diseases that impede healthy growth. Using Deep Learning techniques, cotton plant leaf health status is identified. The main evaluation is the effectiveness of the preprocessing and segmentation methods and the illness classification characteristics. Based on a review of the identification of illnesses using shape- and color-based data, the conclusion is that preprocessing and segmentation procedures play a key role in enhancing accuracy. The SVM, CNN, and ANN were the most widely used classification techniques for diagnosing illnesses. In terms of performance, CNN beat ANN and SVM, according to the poll. According to statistics on the accuracy of several deep learning models, CNN is the most successful model for diagnosing cotton plant leaf illnesses.

The results show that CNN with a convolution layer achieves a higher accuracy 96.25% than ANN and SVM, which were able to achieve 95.47% and 89.06%, respectively.

This work adds to the knowledge on applying transfer learning to identify plant diseases. The study's analysis of the performance of three alternative algorithms reveals the advantages and disadvantages of each strategy. The findings of this study have significant

ramifications for the creation of reliable disease-detection tools that can be used across a range of platforms. This research may find utility in precision agriculture, where early and precise disease diagnosis can increase crop output while lowering pesticide usage. Due to its ability to quickly and effectively monitor crops in the field, mobile device use for plant disease detection has grown in popularity in recent years. Our findings suggest that SSD-Mobile Net is a promising algorithm for this purpose, as it is lightweight and fast, making it suitable for deployment on mobile devices.

On the other hand, SSD-VGG16 is more accurate but slower and heavier, making it more suitable for deployment on high-end servers or desktops. It could be helpful for applications that require high precision, such as disease detection in high-value crops. By providing a clear understanding of the strengths and weaknesses of each algorithm, this study can inform the development of disease detection systems tailored to specific needs and requirements.

This study sheds important information on the application of transfer learning for plant disease diagnosis and emphasizes the significance of taking speed, accuracy, and the deployment platform into account when choosing an algorithm. Our findings have significant ramifications for scientists and professionals involved in the identification of plant diseases as well as those with a general interest in transfer learning for computer vision applications.

Additionally, our outcomes demonstrate that Faster R-CNN-VGG16 performed better in accuracy than SSD-VGG16 and SSD-Mobile Net, reaching an accuracy score of 85.01. This algorithm was less suited for mobile devices or low-power systems since it was the slowest and heaviest of the three.

Overall, the study's findings highlight the significance of choosing the appropriate algorithm for the application's demands and specifications. Our results offer important recommendations to academics and practitioners working on computer vision applications more generally, as well as those designing plant disease monitoring systems. One may create effective and efficient disease detection systems that can increase agricultural productivity and lower the need for pesticides by utilizing the benefits of transfer learning and carefully considering elements like speed, accuracy, and deployment platform.

Plant infections can severely impact crop production and quality, making plant disease protection an essential part of agriculture. Detecting and identifying minute pests on leaves and distinguishing the damaged area of the leaves can be complex tasks for farmers. The study aimed to create a model that can rapidly and effectively identify the type of illness affecting cotton leaves regardless of environmental factors such as lighting and backdrop. A model was developed and tested using photographs of cotton leaves damaged by diseases such as leaf spots, aphid attack, bacterial blight etc. The collection was meticulously chosen to include a wide range of environmental variables and illnesses kinds. The model's output recognizes the name of the disease in the affected region and accurately identifies it.

In summary, a promising strategy for enhancing plant disease protection is the creation of deep learning-based models to identify and distinguish different forms of Cotton leaf diseases automatically. Using instance segmentation, the main goal of identifying numerous leaf diseases is accomplished. Mask RCNN helps farmers to take focused steps to preserve their crops and to increase yields and crop quality by correctly identifying disease types and afflicted areas. This investigation can help both farmers and consumers by advancing the development of potent plant disease defense mechanisms. Future applications could include automated pesticide and fertilizer recommendations based on soil characteristics, weather, and a specific disease, with an increase in the number of projected diseases.

Chapter 6

Future Research Contribution

This chapter presents future research avenues, potential extensions of the work described in the thesis, and some ideas for building on the work already done. The following issues require attention.

- The current phase aims to help the cotton farmer by identifying the disease faster to reduce the effort and economic loss. In the future scope, the application can be expanded for other plants and even fruits by identifying the disease and providing an efficient cure where the plants and disease will vary, but the process will remain the same.
- This project aims to provide farmers with a hardware device at the cheapest rate to help them grow financially. In the future, this process can be available in the Android application and even on the website for identifying and providing a cure for the disease. It will make the technology easily accessible to farmers across the countries.
- Some infections (for example, citrus canker) develop different symptoms as the illness worsens. It becomes more challenging to detect and identify. Very little study has been done on the various stages of the disease. Working on diseases that show such changing symptoms could be a challenge.
- Most of the research is on balanced data. What if the data is unbalanced and if the disease has a smaller number of data points? It could be a good topic to discover more about this.

- In the future, GAN Self-attention network can be used to enhance data size and improve the accuracy of current algorithms.

List of Publications

Publications:

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